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DEVELOPMENT OF A PREDICTIVE MODEL OF LANDSCAPE AESTHETICS

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Final Report
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Development of a Hierarchical Model of Landscape Aesthetics

between
University of Arizona
and
Rocky Mountain Research Station

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In addition to the following report, the work completed under cooperative agreement 28-C2-634 includes two CD-ROMs containing digitized photos and accompanying data of forest scenes used in the estimation of current and prior scenic beauty models. Copies of these CDs are on file in Tom Brown's office at the Rocky Mountain Research Station in Fort Collins.

Development of a Predictive Model of Landscape Aesthetics: Final Report

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Introduction

For over twenty-five years, the United States Forest Service has sponsored empirical research on public perceptions of landscape scenic quality. In an effort to integrate visual quality with other natural resources, much of this research concentrated on using the structural characteristics of forests currently employed by foresters to manage national forests (Ribe, 1989; Daniel, 1990). Not only has this body of research elevated both understanding and sensitivity toward amenity resource values, but has also provided information required under multiple-use forest management principles about the relationship between visual aesthetic resources and other forest resources (Brown, 1981, 1987).

An empirical method commonly used in measuring landscape preferences of the public is the Scenic Beauty Estimation (SBE) method (Daniel & Boster, 1976). In the SBE method, expressed preferences for landscapes are adjusted for individual judgment/rating criteria, and the resulting interval scale values are regressed on quantifiable forest characteristics of the landscape. Such research has successfully yielded statistical models able to predict stated preferences of naive observers specifically for stand-level multiple-use management decision-making (Daniel, 1990).

The SBE method has been applied to numerous forest management practices ranging from differences between harvesting methods (e.g., Daniel & Boster, 1976; Benson & Ullrich, 1981), postharvest treatments (e.g., Arthur, 1977; Brown & Daniel, 1984), silvicultural techniques (e.g., Brush, 1979; Hull & Buhyoff, 1986), and fire and insect damage (e.g., Taylor & Daniel, 1984; Buhyoff & Leuschner, 1978). In addition, the SBE method has been employed in numerous forest types including southwestern ponderosa pine forests (Brown & Daniel, 1984), northeastern hardwood forests (e.g., Brush, 1979), southern pine and oak forests (Ruddell et al., 1989), and northern hardwood forests (Ribe, 1990).

The success of the SBE method is attributable to the reliability, validity, and sensitivity of the measure to differences in perceived scenic quality and the utility of the statistical models to forest managers. However, the applicability of these models is typically limited to the distinctive landscape type and forest conditions on which the particular model is based. Hence, predictive models typically generalize well within the area in which they were developed, but they can not consistently and reliably be generalized to other landscape types or forest conditions (Ribe, 1989). This problem is compounded by the fact that forest resource managers and researchers collect different mensuration data based on the type of forest characteristics either present or of interest to the research needs at the time. Furthermore, there is no common standard for data collection of biophysical variables in how the inventory area is demarcated (e.g., cone or radius plots) nor how a particular characteristic is quantified (e.g., pounds per acre, cubic feet, area percentage).

Because predictive models of amenity resource value are typically valid only within a particular landscape type or set of forest conditions, different models emerge from study to study (Ribe, 1989). Each model is able to predict and explain scenic preferences for specific forest conditions, but does not provide a basis on which to investigate general or mediating factors that are not landscape specific. The identification of common factors, directly associated with specific forest characteristics, would provide complementary understanding of forest visitors' aesthetic experience to forest managers for regional scale planning and management.

Method

In order to develop a predictive model relating scenic quality to forest stand conditions and characteristics that is not restricted to a single forest type, the method of research must provide some basis upon which common factors can be reliably identified, specified, and estimated. This method must also remain sensitive to the original biophysical data, even though the data sets may differ in stand age, variety of species, density, and ground cover.

A confirmatory factor analysis design could provide a foundation upon which factors within each forest type could be used to construct common factors across forest types. Factor analyses could be conducted first within each forest type to determine what factors explain preferences within that type, and would provide comparisons to previously reported within forest type models. A second-order factor analysis could then be run across forest types to determine if any common factors exist that transcend individual forest stand conditions and characteristics.

Common factors so identified could then be modeled using a structural equations modeling or causal analysis procedure. This procedure specifies relationships between the common factors, between common factors and forest specific factors, and between forest specific factors and the original biophysical data for each forest stand. The result of such an analysis would provide a detailed model that identifies common factors, specifies all of the interrelationships, and estimates the strength and direction of those parameters.

A confirmatory factor analysis/structural equations modeling approach has several unique advantages over multiple regression and other possible analyses. A recognized problem with multiple regression type analyses is multicollinearity, or pre-existing correlations between the independent variables. Although its effects can be somewhat mitigated if the experimenter is aware

of the inter-correlations, multicollinearity cannot be eliminated from a regression design. The confirmatory factor analytic approach, however, capitalizes on common or shared variance between variables in order to specify and estimate model parameters. Hence, structural equations models are able to reliably and accurately partition trait variance (e.g., molar forest features) and unique variance (e.g., specific forest characteristics).

Another advantage of the confirmatory factor analysis/structural equations modeling approach is multiple confirmation of model specifications. In exploratory analyses, the specification and estimation of parameters is based on that mathematical combination which best predicts the sample data, which can lead to minor variations in parameters across different runs of the same model. In the proposed approach, multiple levels of confirmation are built into the design to ensure that the resulting common factor model is a stable solution.

Objectives

The intent of this research was to organize a database of multiple within forest type predictive models, and determine whether common factors that transcend within forest conditions and characteristics can be identified using a structural equations modeling approach. Hence, the initial task was to locate and obtain forest stand and perceptual preference data and duplicate sets of slides from researchers who have developed scenic-stand predictive models. Then all the data sets needed to be rendered into a common format and integrated into a single, hierarchical database for analysis. The intent of this objective was to provide a permanent, reproducible, and easily transportable (e.g., compact disk) format to facilitate additional research in the community of landscape preference researchers.

Initial factor analyses within landscape types and hierarchical factor analyses across forest types would be calculated. The resultant factors from exploratory analyses would then serve as input to a structural equations causal modeling analysis in order to link mediating variables of forest stand data across forest types. Finally, a review and comparison of the statistical approaches used in developing predictive models would illuminate the similarities and differences of models developed both within and between forest types.

Procedure

After an extensive literature review of published journal articles and federal research reports, a list of 31 researchers who had conducted research investigating human perceptual responses to varying types of forest characteristics was compiled. The complete list of researchers contacted for the current study is presented in Appendix A. A letter was drafted to solicit participation, which outlined the research goals of the project, specified the necessary qualities for stimuli and data, and offered an incentive (viz., copies of the entire compiled stimulus sets and data bases) for participation. A copy of this letter is presented in Appendix B.

A total of fifteen responses to the mailing were received, or approximately a 50% return rate. Ten of the researchers indicated that they neither had stimulus sets nor data which met the project requirements. Regrettably, four active psychophysical researchers were part of this group, and were unable to contribute due to lost/misplaced data or damaged/discarded slides. Five researchers indicated that they had stimuli and data which conformed to the guidelines specified in the letter, and were willing to contribute to the project. After an additional four months of phone/mail contact with these five volunteers, only three researchers eventually contributed slides and data: Drs. Paul Gobster, Jim Palmer, and Robert Ribe.

Participant slide sets and Multi-Resource Inventory (MRI) slides from one of the author's archives (Brown & Daniel, 1984, 1986) were collected at the University of Arizona for transportation to an official Kodak photo-CD merchant to be digitized. However, several sets of slides were lost in transport by the United Airlines Air Express, including all 180 of Dr. Ribe's slides, an extra set of Dr. Palmer's slides, and numerous MRI slides. This disaster was undeniably—and painfully--ironic, because the one of the major goals of the project was to preserve fragile, vulnerable slides in a longer-lasting, durable medium.

The three remaining sets of slides included a copy of Dr. Gobster's slides (NEMODEL), the original copies of Dr. Palmer's slides (SEASON), and additional MRI slides. Complete information regarding number of slides, sampling procedures, and collected forest mensuration data for the three remaining slide sets is reported in Appendices C, D, and E. However, a brief introduction to each participant slide/data set is presented in the following sections.

NEMODEL Slide and Data Set. Thirty-three areas were photographed from Northeast Forest Experiment Station study sites as part of an aesthetic assessment pilot project in the development of the Northeast Decision Model. Between 1 and 4 photographs were taken from each area, yielding a total of 88 slides. Forest mensuration data for each site were collected by site. Subjects rated each slide for "scenic quality," and these ratings were then averaged across subjects and across the slides comprising each site. Descriptive data and Ns for the 15 biophysical variables are provided in Table 1.

Table 1. NEMODEL Data Set Descriptive Statistics

Variable	N	Mean	SD	Min	Max
BA	83	85.09	46.97	7.50	192.00
BA11	76	54.05	36.65	.00	150.60
BA17	54	26.84	32.32	.00	116.80
BA6	58	15.36	16.65	.00	78.00
DIAMERCH	54	14.01	3.05	6.80	18.90
MAXDBH	85	23.49	10.55	2.00	50.00
MDIAM	56	12.77	3.96	3.00	18.40
NSEED3	22	6997.73	6614.55	2200.00	21800.00
NSEED5	22	3486.36	3773.38	800.00	17900.00
NSEEDAC	37	32854.49	25477.48	11.00	96600.00
NTREES6	58	367.90	380.79	.00	1590.00
Q	9	1.33	0.05	1.30	1.40
QUADIAM	54	8.46	3.01	1.70	13.10
RELDENS	57	56.81	25.53	10.00	100.00
TREESAC	80	290.55	318.90	14.00	1433.00

SEASON Slide and Data Set. 23 views representing six sites in upstate New York were photographed during each season (Spring, Summer, Fall , Winter) of the year. Mensuration data were collected from a 64 degree wedge that began at the photo point and was 30 meters deep. Slides were rated for the "scenic value" by the same group of students four times over a one year period. Descriptive data for the 16 biophysical variables are provided in Table 2.

Table 2. SEASON Data Set Descriptive Statistics

Variable	Mean	SD	Min	Max
BASAL	76.97	25.20	35.92	124.19
CROWN	65.09	12.01	35.92	84.00
DOWNED	93.83	69.33	38.00	321.00
FAR	25.65	18.72	5.00	86.00
GROUND	59.00	14.69	21.00	84.00
HI	7.09	14.54	.00	45.00
LGSAW	1.00	1.17	.00	4.00
LO	86.74	58.33	38.00	285.00
MID	32.26	25.46	12.00	126.00
NEAR	28.83	24.81	9.00	119.00
POLE	6.83	4.60	2.00	23.00
RESID	62.61	11.37	50.00	90.00
SAPLING	214.87	133.05	62.00	526.00
SMSAW	3.52	2.13	1.00	8.00
TIME	8.70	4.06	1.00	13.00
UNDER	21.91	14.62	6.00	56.00

Note. N=23.

MRI Slide and Data Set. 23 designated stands of homogenous forest cover were identified from the Woods Canyon and Bar-M Watersheds on the Coconino National Forest in Northern Arizona. Within each stand, 15 equidistant sample points were determined, and 163 biophysical characteristics were inventoried at approximately 277 points using radial plot demarcation. Four photos were taken in randomly determined directions separated by 90 degrees. Slides were subsequently rated for "natural scenic beauty" and Scenic Beauty Estimates (SBEs) were computed for each slide. Average SBE values over the 4 slides at each point (PTSBE) were then related to the biophysical inventory data for that point to develop SBE models. Descriptive data for the 57

biophysical variables used in subsequent analyses are provided in Table 3.

Table 3. MRI Data Set Descriptive Statistics

Variable	N	Mean	SD	Min	Max
BASOIL	277	3.47	6.91	.00	56.60
BJ	277	516.54	557.29	.00	4897.49
BRUSH	277	10.89	10.00	.00	44.00
CC	277	53.81	24.60	.00	96.90
CCFORB	277	4.86	5.78	.00	35.00
CCGANDF	277	9.42	9.63	.00	54.80
CCGANDS	277	6.21	5.89	.00	37.40
CCGRASS	277	4.56	4.84	.00	32.60
CCSHRUB	277	1.65	3.22	.00	30.00
CCTOTAL	277	11.05	10.31	.00	54.90
COB	277	4.44	5.46	.00	33.10
CVDW	277	1.05	1.55	.00	2.46
DW	277	5.95	4.39	.00	25.00
FPANAT	277	765.57	658.87	.32	3122.23
FPATOT	277	1403.03	1193.33	42.23	8601.91
GFS	277	2.09	2.75	.00	24.00
GRAV	277	1.80	3.03	.00	33.00
GROSSBF	277	10417.42	6368.67	312.12	36756.21
GROSSFT3	277	2724.02	1461.12	138.36	8791.34
HGTFORB	277	7.31	4.90	.00	24.00
HGTGRASS	277	7.45	4.89	.00	23.30
HGTMAX	270	10.33	6.30	.80	38.30
HGTSHRUB	277	4.06	6.51	.00	38.30
IASP	277	5.09	2.32	1.00	9.00
ISLOPE	277	14.55	10.42	.00	40.00
ITS	277	2.50	.84	.00	4.00
ITG	277	2.05	.90	.00	4.00

Table 3. MRI Data Set Descriptive Statistics (Continued)

Variable	N	Mean	SD	Min	Max
OA12PLUS	277	7.36	10.97	.00	66.49
OA512	277	18.90	46.67	.00	445.15
OA5PLUS	277	26.26	51.55	.00	484.89
OAKBA	277	19.32	26.15	.00	186.55
OALT5	277	1232.13	1636.46	.00	8100.00
OATOTAL	277	1258.39	1651.19	.00	8104.13
PDFORB	247	44.58	45.37	.00	265.50
PDGANDF	247	70.23	64.40	.00	357.60
PDGANDS	247	38.02	34.16	.60	224.30
PDGRASS	247	25.65	24.70	.00	139.10
PDSHRUB	247	12.37	21.16	.00	199.20
PDTOTAL	247	82.60	70.36	.60	370.70
PP1224	277	45.46	39.26	.00	198.03
PP144	277	292.78	484.94	.00	4100.00
PP24PLUS	277	3.42	3.76	.00	18.23
PP512	277	151.74	134.89	.00	726.60
PP5PLUS	277	200.62	144.66	2.18	743.19
PPBA	277	133.78	68.00	5.00	322.18
PPLT5	277	325.63	536.45	.00	4700.00
STONE	277	1.67	3.62	.00	26.40
STUMPTOT	277	32.67	31.38	.00	210.00
TOTBA	277	153.79	73.50	17.18	382.18
TPAFD	277	3.04	1.75	.62	10.71
TPANAT	277	8.03	6.50	.00	33.31
TPAPCTSL	277	17.66	19.67	.00	87.50
TPASLA	277	6.29	9.18	.00	79.10
TPATOT	277	14.33	11.46	.61	82.16
TREE	277	1.10	1.69	.00	8.80
YELL	277	9.70	14.26	.00	76.54

Biophysical data was requested from participants in ASCII format for data entry into a common statistical package (SPSS). However, a variety of file options was still present among the three data sets submitted. For example, no common platform was pre-established--two of the data sets were IBM-compatible and one was Macintosh. In addition, the variety of file saving options for ASCII files was also not pre-established--two data sets were tab delimited and one was space delimited. Considerable effort was expended to organize existing data files into comparable data files across the three participant data sets.

Results

Factor Analyses

In order to determine whether common variance models could be estimated across different models, it was necessary to first explore whether common variance could be reliably produced within each of the three models (NEMODEL, SEASON, and MRI). For each data set, an independent exploratory factor analysis (EFA) was calculated using the forest mensuration data. Each EFA was used as an initial step to identify common factors within each model, reduce the overall number of variables, and provide start estimates for subsequent confirmatory analyses. All EFAs were calculated using the SPSS FACTOR procedure, and the results for each model are presented separately in the following sections.

NEMODEL Exploratory Factor Analysis. Eleven of the fifteen physical variables contained in the NEMODEL data set were analyzed in two independent Principal Components EFAs, one without rotation and one with a Varimax--or orthogonal--rotation to determine the best simple structure. The eleven variables were selected to preserve the highest number of slides included in the analysis (N=54), as the other three variables had large amounts of missing data. Two factors, explaining 85% of the variance, were extracted using a minimum eigenvalue criterion of 1.0. Factor 1 had an eigenvalue of 6.46 and explained 59% of the variance, while Factor 2 had an eigenvalue of

2.88 and accounted for 26% of the variance. The unrotated solution was accepted, because the Varimax rotation was unable to provide adequate simple structure (i.e., uncorrelated factors and simple loading patterns). The factor loadings are presented in Table 4.

Table 4. Factor Loadings for NEMODEL Data Set

Variable	Factor 1	Factor 2
BA	.84	.50
BA11	.87	--
BA17	.70	.61
BA6	--	.63
DIAMERCH	.91	--
MAXDBH	.90	--
MDIAM	.94	--
NTREES6	-.74	--
QUADIAM	.83	-.40
RELDENS	.70	.61
TREESAC	--	.92

Note. N=54. Loadings >.40 reported.

Two additional Principal Components EFAs were calculated for the NEMODEL data in order to include the three variables left out of the main analysis. The second EFA included the variable *Number of Seedlings per Acre* (NSEEDAC), bringing the total number of variables included in the analysis to twelve. Two factors were also extracted using the unrotated solution, and together they explained approximately 92% of the variance. However, the sample size dropped to just 37 scenes, which restricted the variance present in the other eleven variables. A third EFA included two additional variables, *Number of Seedlings* >3' (NSEED3) and *Number of Seedlings* > 5' (NSEED5), and again two factors were extracted explaining approximately 92% of the variance. However, the

sample size was reduced to just 22 scenes. Because the factor patterns remained relatively stable across these three estimations and the need to preserve variation for subsequent analyses, the first exploratory factor analysis solution was accepted.

SEASON Exploratory Factor Analysis. All sixteen physical variables contained in the SEASON data set were analyzed in two separate Principal Components EFAs, one without rotation and one with a Varimax--or orthogonal--rotation to determine the best simple structure. A total of five factors were extracted using a minimum eigenvalue criteria of 1.0, explaining approximately 85% of the variance. Factor 1 had an eigenvalue of 6.85 for 43% of the variance, and Factor 2 had an eigenvalue of 2.42 for 15% of the variance. Factors 3, 4, and 5 had eigenvalues of 1.82, 1.39 and 1.10, respectively explaining 11%, 9%, and 7% of the total variance.

The Varimax rotated solution also extracted the same five factors; however, it did not improve interpretability, nor did it sufficiently reduce factor intercorrelations. Hence, the unrotated factor solution was accepted, and the factor loadings are presented in Table 5.

Table 5. Factor Loadings for SEASON Data Set

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
BASAL	.53	.58	--	--	.46
CROWN	.41	.58	--	--	--
DOWNED	.97	--	--	--	--
FAR	.74	--	-.40	--	--
GROUND	--	-.55	--	.54	--
HI	.80	--	--	--	--
LGSAW	--	--	.44	.58	--
LO	.95	--	--	--	--
MID	.88	--	--	--	--
NEAR	.78	--	.48	--	--
POLE	.58	--	--	--	--
RESID	.40	--	.77	--	--
SAPLING	-.54	.69	--	--	--
SMSAW	.62	--	--	--	--
TIME	-.65	.45	--	--	--
UNDER	-.52	.71	--	--	--

Note. N=23. Loadings >.40 reported.

MRI Exploratory Factor Analysis. 57 of the possible 163 possible physical variables contained in the MRI data set were analyzed in two separate Principal Components EFAs, one without rotation and one with a Varimax (orthogonal) rotation to determine the best simple structure. Fifty-seven variables were selected instead of the entire data set to better allow for interpretability of the resultant factors, because many of the selected variables were arithmetic combinations of individual variables previously computed by the authors (see Brown & Daniel, 1984). Fourteen factors, explaining 82% of the variance, were extracted using a minimum

eigenvalue criteria of 1.0. However, only ten are reported, because the last four factors had uniformly small loadings, had no more than two loadings >.40, and contained variables which were factorially complex (i.e., they loaded as high or higher on at least one other factor). The unrotated factor solution was again accepted over the Varimax rotation, because of persistently high factor intercorrelations. The eigenvalues and variance explained for the accepted model for the MRI data is presented in Table 6.

Table 6. Extraction Information for MRI Factor Analysis

Factor	Eigenvalue	% Variance	Cumulative
1	13.32	23%	23%
2	6.29	11%	34%
3	5.40	9%	44%
4	3.63	6%	50%
5	3.29	6%	56%
6	2.63	4%	61%
7	2.23	4%	64%
8	1.97	3%	68%
9	1.88	3%	71%
10	1.51	3%	74%

The factor loadings for the MRI data are displayed in Table 7. However, five variables—*Number of Black Jack Pines* (BJ), *Tree Stories* (ITS), *Total Number of Stumps per Acre* (STMUPTOT), *Stone Ground Cover* (STONE), and *Fuel Depth* (TPAFD) were removed from the table, because they did not load >.40 on any of the ten accepted factors.

Table 7. Factor Loadings for MRI data

Variable	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
ISLOPE	-.55	--	--	--	--	--	--	--	--	--
TOTBA	-.71	--	.45	--	--	--	--	--	--	--
PPBA	-.70	--	.42	.45	--	--	--	--	--	--
OAKBA	-.65	.64	--	.56	--	.41	--	--	--	--
GROSSFT3	-.47	--	--	.60	--	--	--	--	--	--
YELL	--	--	--	--	--	--	.53	--	--	--
CC	-.62	--	--	--	--	--	--	--	--	--
ITG	.42	--	--	--	--	--	--	--	--	--
CCGRASS	.80	--	--	--	--	--	--	--	--	--
CCFORB	.72	--	--	--	--	--	--	--	--	--
CCSHRUB	--	.55	.42	--	--	--	--	.41	--	--
CCTOTAL	.83	--	--	--	--	--	--	--	--	--
PDGRASS	.84	--	--	--	--	--	--	--	--	--
PDFORB	.77	--	--	--	--	--	--	--	--	--
PDSHRUB	--	.46	--	--	--	--	--	--	--	--
PDTOTAL	.88	--	--	--	--	--	--	--	--	--
HGTGRASS	.81	--	--	--	--	--	--	--	--	--
HGTFORB	.74	--	--	--	--	--	--	--	--	--
HGTSHRUB	--	.53	.48	--	--	--	--	--	--	--
HGTMAX	.73	--	--	--	--	--	--	--	--	--
GRAV	--	--	-.55	--	--	--	--	--	--	--
COB	--	--	-.50	--	--	--	--	--	--	--
BASOIL	.44	--	--	--	--	--	--	--	--	--
OLIT	-.44	--	.48	--	--	--	--	--	--	--
DW	--	-.52	--	--	--	--	--	--	--	--
GFS	.57	--	--	--	--	--	--	--	--	--

Table 7. Factor Loadings for MRI data (Continued)

Variable	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
TREE	--	--	--	--	--	--	--	--	.44	--
BRUSH	--	--	--	--	--	-.48	--	--	--	--
TPAPCTSL	.47	--	--	--	--	--	--	--	--	--
TPANAT	--	-.45	.44	--	--	--	--	.40	-.47	--
TPASLA	--	-.64	--	--	--	--	--	--	.48	--
TPATOT	--	-.73	.48	--	--	--	--	--	--	--
FPANAT	--	-.45	.44	--	--	--	--	.41	-.46	--
FPASLA	--	-.63	--	--	--	--	--	--	.49	--
FPATOT	--	-.72	.48	--	--	--	--	--	--	--
IASP	-.43	--	--	--	--	--	--	--	--	--
PPLT5	--	--	--	--	.89	--	--	--	--	--
PP5PLUS	-.54	--	--	--	--	--	-.42	--	--	--
PP512	--	--	--	--	--	--	-.45	--	--	--
PP1224	-.61	--	--	--	--	--	--	--	--	--
PP24PLUS	--	--	--	.46	--	--	--	--	--	--
PP144	--	--	--	--	.90	--	--	--	--	--
OALT5	--	--	.40	--	--	--	--	--	--	.43
OA5PLUS	--	.63	--	--	--	.43	--	--	--	--
OA512	--	.60	--	--	--	.41	--	--	--	--
OA12PLUS	--	.45	--	--	--	--	--	--	--	--
OATOTAL	--	--	.40	--	--	--	--	--	--	.42
PDGANDF	.87	--	--	--	--	--	--	--	--	--
PDGANDS	.78	--	--	--	--	--	--	--	--	--
CCGANDF	.84	--	--	--	--	--	--	--	--	--
CCGANDS	.73	--	--	--	--	--	--	--	--	--

Note. N=247. Loadings >.40 reported.

Confirmatory Factor Analyses

The exploratory factor analyses demonstrated that common variance factors could be identified within each forest structure data set, as each explained acceptable proportions of variance (85%, 85%, and 74%) and produced similar variable to factor ratios (viz., 1.8:1, 3:1, 1.7:1). The accepted factor structure for each data set was then transferred to latent variable loading patterns for each model in a confirmatory factor analysis (CFA) or structural equations modeling approach. The intent was to pre-establish a refined measurement model for all of the biophysical variables within each data set before associating these factors with the criterion--scenic quality.

Three separate CFAs were calculated using EQS (Bentler, 1995). Covariance matrices were constructed using the respective number of biophysical variables identified in the EFAs, and measurement equations were entered identifying the predicted associations between variables and latent factors (i.e., strength and direction of relationship). The NEMODEL data set converged on a solution in seven iterations, which was well within the recommended ideal of fifteen (Bentler, 1995). However, all three of the fit indices (Bentler-Bonnett Normed Fit Index =.47, Bentler-Bonnett Non-Normed Fit Index =.46, and Comparative Fit Index=.62) were well below accepted norms (>.90). Furthermore, four of the eleven variables failed to represent a significant proportion of variance to their respective factors, and were subsequently dropped from the CFA. Numerous modifications to the factor structure failed to improve these fit indices to acceptable levels.

For the SEASON and MRI data sets, the measurement models were not estimated, as both matrices were reported by in the EQS output to be "not positive-definite." This error can result from at least two logically different conditions: (1) a mis-specified model or (2) linear dependencies amongst the data. Bentler (1995) suggests using an initial EFA to pre-determine the underlying

factor structure and avoid mis-specifying a model. As both data sets directly incorporated the measurement models identified in the EFAs, this recourse had already been exhausted. EQS also offers a multi-sample analysis which can correct for systematic missing data and linear dependencies if enough independent data sets can be identified such that such problems are ameliorated across all data sets. This, however, was not a possible solution, as only three data sets comprised the present analysis.

Despite the promise of the CFA approach to systematically identify both common and unique variance for explanation and prediction, acceptable measurement models for all three data sets were not produced. Although additional data sets may resolve the issue of missing data, the complexity of the interrelationships amongst the biophysical data may preclude the accurate estimation of these models. As this is fundamentally an empirical question, further research is required to address these concerns.

Variable and Factor Score Multiple Regression Analyses

Although the CFA approach was not a productive as originally envisioned, three independent EFAs were able to generate acceptable factor structures. These results may provide indications of a hierarchical model of landscape preference, and may still prove useful in the present study. Consequently, factor scores were generated within each data set using the SPSS Factor procedure. Factor scores are linear composites of the variables which comprise a factor, and are weighted by the strength of the respective factor loading and communality--or reliable variance (Gorsuch, 1983). As with stand-level biophysical variables, these factor scores could then be used to predict the scenic value of the represented areas. Multiple regression equations were subsequently calculated within each data set using both the originally available biophysical data and the respective factors generated

from the EFA.

The general procedure for each data set was to initially enter all of the variables as a block using the SPSS Linear Regression procedure. This provided information about the entire model (overall R^2 and adjusted R^2), but did not address issues of multicollinearity (i.e., correlated predictors) nor autocorrelation (i.e., correlated residuals). Pedhazur (1982) suggests that a hierarchical stepwise selection procedure be used, which enters variables according to pre-established theoretical or empirical criteria. After the initial block entry regression was estimated, two separate regression equations were calculated using the default stepwise criteria in SPSS (i.e., $p<.05$ for entry and $p>.10$ for removal). The first stepwise equation used the descending size of the zero-order correlation of each predictor to the criterion to establish entry order, while the second stepwise equation used the descending size of the partial correlation of each predictor to the criterion. In most cases, linear variable functions were given precedence over non-linear functions unless previously identified in prior research. If non-linear functions were identified for specific variables, the Curve Fitting procedure in SPSS was used to determine the best fit (i.e., adjusted R^2).

NEMODEL Multiple Regression. Initially, all eleven variables were entered as a block of predictors for SBE, which produced a regression model with an R^2 of .65 and an adjusted R^2 of .49. Nine of the eleven variables had statistically significant partial correlations. Two stepwise multiple regression equations were then calculated. For the first equation, the five variables that had the highest zero-order correlation with the criterion (SBE) were entered from highest to lowest. *Basal Area* (BA) was the first variable entered, and none of the other four variables met the entry criterion for inclusion. The BA model had a R^2 of .47 and an adjusted R^2 of .46. For the second equation, the five variables that had the highest partial correlation with the criterion (SBE) were entered from

highest to lowest. *Basal Area of Trees > 17" dbh* (BA17) was the first variable entered, and none of the other four variables met the entry criterion for inclusion. The BA17 model had a R^2 of .45 and an adjusted R^2 of .43. Both equations were directly comparable (i.e., no statistically significant difference) to the model statistics of the original regression model with all eleven variables.

In addition, a multiple regression equation was also calculated with the two factors identified in the EFA as predictors and SBE as the criterion. Both the zero-order and partial correlation criteria identified the same order of entry. Hence, a single stepwise multiple regression equation was calculated, and both Factors 1 and 2 were retained. The model had a R^2 of .45 and an adjusted R^2 of .41.

SEASON Multiple Regression. Initially, all sixteen variables were entered as a block of predictors in four separate equations, because each of the four possible criterion variables is based on the seasons from which the image was photographed (viz., Spring, Summer, Fall, Winter). The model statistics for each season are presented in Table 13. In addition, model statistics for the multiple regression equations using all five factors entered as a block are presented in Table 8. The stepwise multiple regression models for both variables and factors, as specified by the zero-order and partial correlation inclusion criteria, are presented separately by season.

Table 8. Initial Model Statistics for SEASON Data Set

	Variable (16)			Factor (5)		
Season	R^2	Adjusted R^2	Se_e	R^2	Adjusted R^2	Se_e
Spring	.83	.59	.38	.46	.30	.50
Summer	.79	.49	.41	.26	.05	.55
Fall	.76	.42	.55	.40	.23	.64
Winter	.88	.69	.40	.55	.42	.55

Note. N=23.

For Spring, a total of three stepwise multiple regression equations were calculated (type of predictor set by order of inclusion). For the variable predictor set, two separate stepwise multiple regression equations were calculated using either the five highest zero-order correlations or the five highest partial correlations with the criterion (SPRING). For the zero-order correlation order, *Number of Stems 6-12"* (POLE) was entered first, and none of the other four variables met the entry criterion for inclusion. The POLE model had a R^2 of .20 and an adjusted R^2 of .16. Although this reduction in number of variables represented a loss of 40% of explained variance, inclusion of variables with non-significant independent relationships with the criterion has numerous problems in estimating and fitting model parameters (Pedhazur, 1982). For the partial correlation order, the retained model included three variables: *Number of Stems 6-12"* (POLE), *Downed Wood 20' from Apex* (MID), and *Basal Area* (BASAL). The regression model had an R^2 of .51 and an adjusted R^2 of .43. The regression parameters are presented in Table 9.

Table 9. Regression Parameters for Spring: Variable Predictor Set by Partial Correlation Order Model with Stepwise Inclusion Criterion

Variable	B	Beta	t
POLE	.069	.53	2.78
MID	-.014	-.58	-3.06
BASAL	.016	.45	2.42

Note. N=23.

For the factor predictor set, a multiple regression equation was also calculated with the five factors identified in the EFA as predictors and SPRING as the criterion. Both the zero-order and partial correlation criteria identified the same entry order: *Factor 5, Factor 4, Factor 2, Factor 3,* and

Factor 1. Therefore, a single stepwise multiple regression equation was calculated, and only *Factor 5* was retained. The model had a R^2 of .22 and an adjusted R^2 of .18.

The 3 variable (POLE, MID, BASAL) partial correlation order model for Spring was very similar to the 16 variable block entry model in regard to adjusted R^2 (.43 and .59 respectively). However, the other two models--the zero-order correlation for variables model and the combined order for factors model--were woefully inadequate in predicting the criterion Spring with adjusted R^2 of .16 and .18, respectively.

For Summer, a total of three stepwise multiple regression equations were calculated (type of predictor set by order of inclusion). For the variable predictor set, two stepwise multiple regression equations were calculated using either the five highest zero-order correlations or the five highest partial correlations with the criterion (SUMMER). However, none of the five variables in the zero-order correlation set nor the partial correlation set were retained using the stepwise inclusion criterion (entry $p<.05$). For the factor predictor set, a multiple regression equation was also calculated with the five factors identified in the EFA as predictors and SUMMER as the criterion. Both the zero-order and partial correlation criteria identified the same order: *Factor 5, Factor 1, Factor 2, Factor 3,* and *Factor 4*. Therefore, a single stepwise multiple regression equation was calculated, but none of the five factors were retained using the stepwise inclusion criteria. Palmer and Sena (1992) comment on the difficulty of predicting scenic quality of the summer scenes in the SEASON data set, which they were unable to successfully develop strong predictive model as well.

For Fall, a total of three stepwise multiple regression equations were calculated (type of predictor set by order of inclusion). For the variable predictor set, two separate stepwise multiple regression equations were calculated using either the five highest zero-order correlations or the five

highest partial correlations with the criterion (FALL). For the zero-order correlation order, two variables were retained: *Downed Wood 20-30' from Apex* (FAR) and *Crown Closure* (CROWN). This model had a R^2 of .51 and an adjusted R^2 of .46. The regression parameters are presented in Table 10. For the partial correlation order, *Basal Area* (BASAL) was entered first, and none of the other variables met the entry criterion for inclusion. The BASAL model had an R^2 of .22 and an adjusted R^2 of .18.

Table 10. Regression Parameters for Summer: Variable Predictor Set by Zero-Ordered Correlation Order Model with Stepwise Inclusion Criterion

Variable	B	Beta	t
FAR	.017	.44	2.63
CROWN	.025	.41	2.44

Note. N=23.

For the factor predictor set, a multiple regression equation was also calculated with the five factors identified in the EFA as predictors and FALL as the criterion. Both the zero-order and partial correlation criteria identified the same entry order: *Factor 5, Factor 4, Factor 3, Factor 2,* and *Factor 1.* Therefore, a single stepwise multiple regression equation was calculated, but none of the five factors met the minimum criteria for inclusion.

The two variable (FAR, CROWN) zero-order order model for Fall was very similar to the 16 variable block entry model in regard to adjusted R^2 (.46 and .42 respectively). However, the other two models--the zero-order correlation for variables model and the combined order for factors model--were considerably inadequate in predicting the criterion Fall.

For Winter, a total of three stepwise multiple regression equations were calculated (type of predictor set by order of inclusion). For the variable predictor set, two separate stepwise multiple regression equations were calculated using either the five highest zero-order correlations or the five highest partial correlations with the criterion (WINTER). For the zero-order correlation order, *Number of Years Since Harvest* (TIME) was entered first, and none of the other four variables could meet the entry criterion for inclusion. The TIME model had a R^2 of .52 and an adjusted R^2 of .50. For the partial correlation order, *Understory* (UNDER) was entered first, and none of the other four variables could meet the entry criterion for inclusion. The UNDER model had an R^2 of .34 and an adjusted R^2 of .31.

For the factor predictor set, a multiple regression equation was also calculated with the five factors identified in the EFA as predictors and WINTER as the criterion. Both the zero-order and partial correlation criteria identified the same order: *Factor 1, Factor 2, Factor 4, Factor 3,* and *Factor 5.* Hence, a single stepwise multiple regression equation was calculated, and both *Factor 1* and *Factor 2* were retained. The model had a R^2 of .49 and an adjusted R^2 of .44. The regression parameters are presented in Table 11.

Table 11. Regression Parameters for Winter: Factor Predictor Set by Zero-Ordered and Partial Correlation Order Models with Stepwise Inclusion Criterion

Variable	B	Beta	t
Factor 1	.43	.60	3.78
Factor 2	-.26	-.36	-2.25

Note. N=23.

The zero-order correlation order model included TIME as the only predictor, but had an adjusted R^2 of .52, which was comparable to the overall model with an adjusted R^2 of .69. The factor model also produced a respectable adjusted R^2 of .44. Both of these equations accurately

reflect the important variables identified in Palmer and Sena (1992) for the Winter condition.

MRI Multiple Regression. Rather than running an initial regression model where all 52 variables from the EFA would be entered as a block, the stepwise procedure was adopted from the outset for the MRI data set. Using PTSBE as the criterion, eight variables were selected for inclusion: *Herbage Maximum Height* (HGTMAX), *Number of Ponderosa Pine >24" dbh* (PP24PLUS), *Total Herbage Weight to .75 Power* (PDTOT75), *Number of Ponderosa Pine 5-12" dbh* (PP512), *Number of Oak 5-12" dbh* (OA512), *Percent Ground Cover-Cobble* (COB), *Total Number of Stumps per Acre* (STUMPTOT), and *Inventory Aspect* (IASP). The accepted model had a R^2 of .54 and an adjusted R^2 of .53. The regression parameters are presented in Table 12.

Table 12. Regression Parameters for MRI Variables with Stepwise Inclusion Criterion

Variable	B	Beta	t
HGTMAX	2.15	.36	4.80
PP24PLUS	1.51	.18	3.72
PDTOT75	0.48	.26	3.19
PP512	-0.02	-.11	-2.11
OA512	0.09	.15	3.09
COB	-0.66	-.13	-2.63
STUMPTOT	-0.12	-.13	-2.60
IASP	-1.58	-.12	-2.33

Note. N=248.

In addition, a multiple regression equation was also calculated with the ten factors identified in the EFA as predictors and PTSBE as the criterion. Again, the stepwise selection criteria was used instead of block entry, and *Factor 1*, *Factor 5*, *Factor 9*, *Factor 2*, and *Factor 4* were all retained for the regression equation. The model had a R^2 of .49 and an adjusted R^2 of .48. The regression

parameters are presented in Table 13.

Table 13. Regression Parameters for MRI Factors with Stepwise Inclusion Criterion

Variable	B	Beta	t
Factor 1	18.33	.56	11.36
Factor 5	7.80	.26	5.41
Factor 9	7.32	.24	4.80
Factor 2	-6.33	-.21	-4.35
Factor 4	3.28	.11	2.31

Note. N=242.

A direct comparison of these predictive models to Brown and Daniel (1984, 1986) is difficult, because--in part--of the number of variables originally entered into each model. In the present analysis, all 52 variables were entered either as independent variables or linear composite factor scores, and selection for the final model was based on the stepwise criterion ($p<.05$). Whereas in Brown and Daniel, variables were conceptually divided into a series of models addressing specific stand qualities before entered into a stepwise regression. For example, a basic model exclusively concentrating on plant materials (viz., trees per acre, herbage weight, and volume of downed wood), a detailed downed wood model, and a summary model using gross stand features (viz., total cubic basal area, aspect and tree grouping). Despite these differences, the variables and factors identified in the present analysis bear a striking resemblance to the ones identified in Brown and Daniel.

For the MRI variables model, commonalities with the Brown and Daniel (1984, 1986) models were *Number of Ponderosa Pine >24" dbh* (PP24PLUS), *Total Herbage Weight to .75 Power* (PDTOT75), *Number of Ponderosa Pine 5-12" dbh* (PP512), and *Inventory Aspect* (IASP). For the MRI factors model, commonalities (loadings >.60) with the Brown and Daniel models are presented in Table 14. As can be seen, most of the variables across all three pre-harvest models reported in

Brown and Daniel were identified in either the MRI Variables or Factors models. Furthermore, the resultant R^2 and adjusted R^2 of all models, Brown and Daniel included, were very similar, indicating that differences between variable selection procedures and construction of linear compositions did little to augment or detract from the total amount of explained variance.

Table 14. Matched Variables Between Brown and Daniel Model and MRI Factors Model

Factor 1	Factor 5	Factor 2
Pine Basal Area (PPBA)	Number of Ponderosa Pine <5" dbh (PPLT5)	Oak Basal Area (OAKBA)
Oak Basal Area (OAKBA)	Number of Ponderosa Pine <4.5' high (PP144)	Total Number Downed Wood (TPATOT)
Total Herbage Weight (PDTOT)		Total Volume Downed Wood (FPATOT)
Number of Ponderosa Pine 5-12" dbh (PP512)		
Aspect (IASP)		

Note. Loadings >.60 reported. Factor 9 had no loadings >.60 and Factor 4 had no matching variables.

Matched Sample Multiple Regression. A final method to identify common features across distinctive forest conditions relevant to aesthetic value was to select directly comparable variables across all three data sets. The NEMODEL, however, had the lowest number of variables related to the other two data sets, and was subsequently dropped from this matched sample analysis. The SEASON and MRI data sets shared nine forest characteristic variables. The listing of both sets of variable names and descriptive data are presented in Table 15.

Table 15. Descriptive Statistics of Selected Variables from the MRI and SEASON Data Sets

MRI Variable Name	Mean	SD	SEASON Variable Name	Mean	SD
TOTBA	153.79	73.50	BASAL	76.97	25.20
CC	11.05	24.60	CROWN	65.09	12.01
TPATOTAL	14.33	11.46	DOWNED	93.83	69.33
CCTOTAL	11.05	10.31	GROUND	59.00	14.69
LGSAW (PP20PLUS + OA20PLUS)	8.28	7.40	LGSAW (18-24")	1.00	1.17
SMSAW (PP1220 + OA1220)	47.96	40.09	SMSAW (12-18")	3.52	2.13
POLE (PP512 + OA512)	170.64	139.17	POLE (6-12")	6.83	4.60
SAPLING (PPLT5 + OALT5)	1997.11	2181.57	SAPLING (<6")	214.87	133.05
UNDERSTORY (PP1+PP14+OA1+OA14)	1770.04	2134.35	UNDERSTORY	21.91	14.62

Note. MRI (N=255) and SEASON (N=23).

For the MRI data set, a stepwise multiple regression equation was computed using all nine variables as predictors and PTSBE as the criterion. A total of five variables were retained: *Number of Trees <4" dbh* (UNDERSTORY), *Total Herbage Canopy* (CCTOTAL), *Crown Canopy*(CC), *All Trees >20" dbh* (LGSAW) and *Total Basal Area* (TOTBA). The accepted model had a R^2 of .36 and an adjusted R^2 of .35. The regression parameters are presented in Table 16.

Table 16. Regression Parameters for MRI Matched Sample with Stepwise Inclusion Criterion

Variable	B	Beta	t
UNDERSTORY	0.00	.37	7.27
CCTOTAL	0.85	.25	4.62
CC	-0.22	-.17	-3.02
LGSAW	1.04	.23	4.51
TOTBA	-0.07	-.15	-2.52

Note. N=255.

For the SEASON data set, four separate stepwise multiple regression equations were computed using all nine variables as predictors and the season-appropriate scenic value rating as the criterion. For Spring, only *Number of Trees 6-12" dbh* (POLE) was retained with a R^2 of .20 and an adjusted R^2 of .16. The other eight variables failed to meet the entry criterion ($p<.05$). For Summer, all nine variables failed to meet the stepwise entry criterion, so no variables were retained. For Fall, only *Crown Closure* (CROWN) was retained with a R^2 of .34 and an adjusted R^2 of .30. Again, the other eight variables failed to meet the entry criterion. For Winter, two of the nine variables were retained: *Number of Trees <6" dbh* (SAPLING) and *Transect Stem Count of Downed Wood* (DOWNED). The model had a R^2 of .48 and an adjusted R^2 of .43, and the regression parameters of the model are presented in Table 17.

Table 17. Regression Parameters for SEASON Matched Sample (Winter) with Stepwise Inclusion Criterion

Variable	B	Beta	t
SAPLING	-0.02	-.45	-2.59
DOWNED	0.00	.39	2.26

Note. N=23.

Although the predictors for these two regression models were as closely matched as possible, direct comparison between the MRI and SEASON data sets was wrought with problems because of the different number of dependent measures. Palmer and Sena (1992) have identified differences in the predictive regression models of northeastern deciduous forests based on the season in which the picture was taken. Furthermore, the most directly comparable image and data set to the MRI slides would have been summer, but Palmer and Sena reported the lowest R^2 for summer than any of the other three seasons. This is in part due to the reliance on more stable forest structural variables (e.g., Basal Area, Crown Canopy), which may not reflect the presence of foliage which dominates deciduous stands in the summer. In addition, differences in forest composition and structure are evident in the descriptive statistics presented in Table 15.

Discussion and Conclusion

This was a very ambitious project which sought to accomplish several lofty goals. One important purpose was to identify and collect images and their respective databases from psychophysical projects conducted in the past 25 years in order to preserve and distribute to the community of amenity resource researchers interested in re-analysis and meta-analysis of the same. A secondary purpose of collecting such resources, however, was to pose the question of whether or not a hierarchical model of landscape preference could be generated from the stand-specific information that has been--and is--the norm in landscape aesthetics research. The generalizability of stand-specific models has been questioned repeatedly in the literature, even though some researchers have pointed out the remarkable similarity of these models in terms of forest structure despite differences in forest composition (Ribe, 1989).

The first goal was realized to a moderate degree. Optimally, the ideal was to collect all images and data that had been published using the psychophysical approach. However, a low response rate, coupled with numerous mishaps, resulted in limited success for this objective. Several researchers who have a long history in amenity resource research were unable to participate due to lost/misplaced data or damaged/discarded images. In addition, the loss of Dr. Ribe's images due to transportation malfeasance added insult to injury. The amount of psychophysical research is limited, and not very common. The loss of any data or images is a serious blow to this valuable resource. In the future, it is hoped that amenity researchers and Forest Service co-operatives negotiate an archival system for data and images in order to preserve this information for the scientific community.

The attempts at constructing a hierarchical model of landscape aesthetics also met with marginal success. Although the project was unable to create a stable, predictive model which was generalizable across different landscape types or sets of forest conditions, the promise of this idea still exists; it simply requires the appropriate conditions to germinate and be fully realized. In part, many of the problems encountered were the direct result of not being able to collect an appropriate variety and number of images/databases to override the limitations of stand-specific methodologies. Ultimately, these constraints could not be overcome. However, numerous prospects were revealed.

The exploratory data analyses (EFAs) demonstrated that this technique can be used to create common factors of biophysical variables. Across all three data sets, the EFAs were successful in explaining the majority of the variance present and reducing the number of variables by 33-50%. Most of the factors were interpretable, although at times illustrated the very complex nature of biophysical interrelationships in an ecosystem. The confirmatory factor analyses (CFAs), however, failed outright. This would be an intriguing area of further study: to determine whether or not

reliable common factors of biophysical variables can be statistically generated from theory. In part, the amount of missing data both within and across the three data sets significantly hampered alternative avenues which may have be able to address these problems. Added images and data sets in the future may resolve some of these issues and provide the answer to the question originally proposed.

Follow-up analyses were also moderate in their success. The multiple regression analyses (MR) of the variables merely confirmed previously published material. However, the MR of the factors generated in the EFA were met with varied success, which seemed dependent upon the breath and depth of the variable databases from which they were estimated. The NEMODEL and SEASON databases did not have the amount of biophysical data not the sample size--whether number of sites, points or views--to be able to reliably estimate parameters in the MR analyses. The promise of the hierarchical approach was best demonstrated in the MRI data set, where the MR model based on the factors generated from the EFA was similar in amount of variance explained to previously published results (Brown & Daniel, 1984, 1986) and the stepwise regression model constructed herein. Further investigation with similar sized data sets is warranted based on these results.

In conclusion, we recommend that the research stations of the USDA Forest Service establish some minimal standards for biophysical data collection. These standards should not be so onerous or cumbersome to discourage psychophysical research, but should endeavor to create a nationwide data base which is commensurate in terms of identifying inventory sites, collection of biophysical data, and transferring to an archival format. We recognize that researchers and forest managers collect information which is of use to their immediate concerns, and do not want to discourage such behavior. However, the lack of correspondence amongst amenity resource research is appalling,

especially when minor steps could be taken to correct the situation. The USDA Forest Service Research and Experiment Stations do sponsor much of this type of research, and could easily instigate these necessary reforms.

In addition, an alarming trend in landscape preference research is the gradual decline in number of studies using the psychophysical approach. The time and effort required to create these extensive image/databases has kept their occurrence infrequent at best. As illustrated in this project, such research is a timeless, national treasure which can be reanalyzed as needed and applied as appropriate. Opportunities should be provided to researchers interested in creating such image/databases and support to preserve such information for posterity.

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Appendix A:

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Researcher Contact List

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Tucson, AZ 85721

Appendix B:

Contact Letter

March 8, 1993

X
X
X
X

Dear X,

As a fellow researcher in landscape aesthetics, we are sure you are well aware that there is over twenty-five years of research on public perceptions of natural scenic quality, much of it sponsored by the USFS. Not only has this body of research elevated both understanding and sensitivity toward aesthetic values, but it has provided important information about the relationship between public preferences and biophysical forest characteristics, which has been useful for multiple-use management decision-making on public lands.

The applicability of these results and models is, however, typically limited to the distinctive landscape type and environmental conditions represented by the individual study. Predictive models typically generalize well within a particular landscape type or set of forest conditions, but they can not consistently and reliably be generalized to other landscape types or forest conditions because different models emerge from study to study.

We are initiating a study to develop a hierarchical model of landscape aesthetics that aspires to identify common factors across landscape types and directly associate those factors with specific forest characteristics. In order to conduct such an ambitious project, however, we **need** your help. You have been identified as a researcher who has developed a predictive model of landscape aesthetics for forest or woodland environments. In order to initiate this research project, it is very important that we obtain forest environmental inventory and associated perceptual preference data, as well as original slides from your studies.

The type of materials we are attempting to locate are very specific. We need color slides of forested (or woodland) areas with associated biophysical data (e.g., tree ages, species, density, ground cover, etc.) and, if available, perceptual ratings (e.g., scenic beauty, aesthetic quality, or personal preference) for each scene or set of scenes. For example, the project reported in Brown and Daniel (1984) employed color slides sampled at numerous "points" throughout a number of relatively homogenous forest stands. The four scenes that represented each point had directly corresponding biophysical data (e.g., herbage weight/acre and number or ponderosa pines by diameter at breast height/acre, etc.) and perceptual data (e.g., scenic beauty estimates averaged over the four corresponding scenes). We prefer that the biophysical and perceptual databases be sent to us in an electronic format (e.g., DOS or ASCII type format) on either a 5¼" or 3½" floppy disk.

What will happen to the material you send us? We will duplicate your original slides by sending them to the Kodak imaging labs to be digitized onto optical disks. In the long run, the optical disk medium will save wear and tear on these precious resources and provide a stable archival storage for the images. We will render all data sets sent to us into a common electronic format, and then integrate them into a single database for analysis. All of the material you send to us will be kept secure and returned to you as soon as humanly possible.

What do you get out of this? Other than the altruistic feeling that you have helped colleagues advance the social scientific frontier, you will receive: (1) Kodak compact disks containing all of the scenes submitted to the project (yours and everyone else's) and (2) the data set of all forest characteristic and perceptual preference data in a common electronic format for your own personal use and/or analysis. Every researcher who submits material will be duly credited. We are confident you will agree that the benefits you will receive outweigh the efforts on your behalf to locate, organize, and ship the materials to us.

Please send these requested materials to us **as soon as possible**, or at the latest by May 28, 1993 to be included in this project. All materials submitted to us will be returned to their respective owners by July 15, 1993 along with your image and data disks. If locating, organizing, and sending this material cannot be easily accomplished, we would be happy to assist in any way possible. For instance, it may be feasible to send a representative to your lab to help collect together the slides and data from your experiments.

We appreciate your time, effort, and participation in this important project. Enclosed, please find a reply form, pre-addressed envelope, and an initial contact list. We hope you will accept our invitation to participate. Please send your acknowledgment and any additional persons we should contact at your earliest convenience. If you have any questions or comments, please do not hesitate to contact us via phone, FAX (602) 621-9306, or BITNET "SBELAB@CCIT.ARIZONA.EDU." We look forward to hearing from you.

John Hetherington
Department of Psychology
University of Arizona
Tucson, AZ 85721
(602) 621-9263

Terry C. Daniel
Department of Psychology and
School of Renewable Natural Resources
University of Arizona
Tucson, AZ 85721
(602) 621-7453

Appendix C:

Codebook for MRI Stimulus Set

Title: Multi-Resource Inventory (MRI)
Woods Canyon and Bar-M Slides

Date: 1979-1980

Contact:

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University of Arizona
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Phone: (520) 621-7453
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Thomas C. Brown
Rocky Mountain Forest and
Range Experiment Station
3825 E. Mulberry
Ft. Collins, CO 80524
Phone: (970) 498-1892
Fax: (970) 498-1660

Description:

Woods Canyon (12,000 acres) and Bar-M (16,360 acres) Watersheds on the Coconino National Forest in Northern Arizona were divided into stands (minimum 10 acres) of homogenous forest cover (predominantly ponderosa pine) by US Forest Service personnel using standard photo-interpretation and ground truthing techniques. Within each of 23 designated stands, 15 equidistant sample points were determined. At each point biophysical characteristics were inventoried using standard methods and 4 color slide photos (Kodachrome ASA 64) were taken in randomly determined directions separated by 90 degrees. Slides were subsequently rated for "natural scenic beauty" and Scenic Beauty Estimates (SBEs) were computed for each slide. Average SBE values over the 4 slides at each point (PTSBE) were related to the biophysical inventory data for that point to develop SBE models.

Citations:

Brown, T.C., & Daniel, T.C. (1984). Modeling forest scenic beauty: Concepts and applications to ponderosa pine (RM-256). Ft. Collins, CO: Rocky Mountain Forest and Range Experiment Station.

Brown, T.C., & Daniel, T.C. (1986). Predicting scenic beauty of timber stands. Forest Science, *32*, 417-487.

Variable List

Varname	Variable Name	Measurement
PH_LABEL	Photo Label	nominal
ICOMP	Compartment	(502-539)
IST	Stand	(1-98)
IPT	Point	(1-15)
IPROC	Inventory Procedure	(1-2)
IMO	Inventory Month	(5-May to 8-August)
IYEAR	Inventory Year	(1979 or 1980)
IACRES	Inventory Acreage	(21-148 acres)
IELEV	Inventory Elevation	(6480-7600ft)
ISLOPE	Inventory Slope	(0-40 degrees)
IASPECT	Inventory Aspect	(1-9)
IMECH	Mechanical Disturbance	(0-65%)
IDC		
TOTBA	Total Basal Area	(17-382 ft^2/acre)
PPBA	Ponderosa Pine Basal Area	(5-322 ft^2/acre)
OAKBA	Oak Basal Area	(0-186 ft^2/acre)
GROSSFT3	Gross Pine Volume	(138-8791 ft^3/acre)
GROSSBF	Gross Pine Board Feet	(312-36,756 bf/acre)
PP1	Ponderosa Pine < 1ft tall	(0-1300 no./acre)
PP14	Ponderosa Pine 1-4.5ft tall	(0-1500 no./acre)
PP4	Ponderosa Pine 4.5ft to 4.9" dbh	(0-2600 no/acre)
PP59	Ponderosa Pine 5-9" dbh	(0-690 no./acre)
PP912	Ponderosa Pine 9-12" dbh	(0-247 no./acre)
PP1216	Ponderosa Pine 12-16" dbh	(0-176 no./acre)
PP1620	Ponderosa Pine 16-20" dbh	(0-61 no./acre)
PP2024	Ponderosa Pine 20-24" dbh	(0-30 no./acre)
PP2428	Ponderosa Pine 24-28" dbh	(0-14 no./acre)
PP28	Ponderosa Pine > 28" dbh	(0-10 no./acre)
BJ	Black Jack	(0-4897 no./acre)
YELL	Yellow Pine	(0-76 no./acre)
CC	Crown Canopy	(0-97%)
ITS	Tree Stories	(1-4 rating)
ITG	Tree Grouping	(1-4 rating)
OA1	Oak < 1ft tall	(0-7900 no./acre)
OA14	Oak 1-4.5ft tall	(0-4900 no./acre)
OA4	Oak 4.5ft to 4.9" dbh	(0-10000 no./acre)
OA59	Oak 5-9" dbh	(0-407 no./acre)
OA912	Oak 9-12" dbh	(0-79 no./acre)
OA1216	Oak 12-16" dbh	(0-60 no./acre)
OA1620	Oak 16-20" dbh	(0-29 no./acre)
OA2024	Oak 20-24" dbh	(0-27 no./acre)

OA2428	Oak 24-28" dbh	(0-11 no./acre)
OA28	Oak > 28" dbh	(0-4 no./acre)
OT1	Other Trees < 1ft tall	(0-3200 no./acre)
OT14	Other Trees 1-4.5ft tall	(0-6500 no./acre)
OT4	Other Trees 4.5ft to 4.9" dbh	(0-200 no./acre)
OT59	Other Trees 5-9" dbh	(0 no./acre)
OT912	Other Trees 9-12" dbh	(0 no./acre)
OT1216	Other Trees 12-16" dbh	(0 no./acre)
OT1620	Other Trees 16-20" dbh	(0 no./acre)
OT2024	Other Trees 20-24" dbh	(0 no./acre)
OT2428	Other Trees 24-28" dbh	(0 no./acre)
OT28	Other Trees > 28" dbh	(0 no./acre)
STUMPSM	Small Stumps 1-4" at top	(0-140 no./acre)
STUMP512	Stumps 5-12" at top	(0-100 no./acre)
STUMP122	Stumps 12-20" at top	(0-50 no./acre)
STUMP20	Stumps >20" at top	(0-60 no./acre)
STUMPTOT	Total Stumps	(0-210 no./acre)
CCGRASS	Grass	(0-33%)
CCFORB	Forbs	(0-35%)
CCSHRUB	Shrubs	(0-30%)
CCTOTAL	Total	(0-55%)
PDGRASS	Grass herbage weight	(0-139 lbs.)
PDFORB	Forbs herbage weight	(0-265 lbs.)
PDSHRUB	Shrubs herbage weight	(0-199 lbs.)
PDTOTAL	Total herbage weight	(.6-371 lbs.)
HGTGRASS	Grass maximum height	(0-23 inches)
HGTFORB	Forbs maximum height	(0-24 inches)
HGTSHRUB	Shrubs maximum height	(0-38 inches)
GRAV	Gravel, % ground cover	(0-33%)
COB	Cobble, % ground cover	(0-33%)
STONE	Stone, % ground cover	(0-26%)
BASOIL	Bare Soil, % ground cover	(0-57%)
OLIT	Litter, % ground cover	(31-98%)
DW	Dwn Wood, % ground cover	(0-25%)
GFS	Grasses, Forbs, Shrubs, grnd cover	(0-24%)
TREE	Tree, % ground cover	(0-9%)
BRUSH	# Brush Piles	(0-44/acre)
SI	Stand Site Index	(See Minor, 1964)
SIAV		
TPA0	Dwn Wood, <.25" diameter	(0-.6/acre)
TPA114	Dwn Wood, .25-.9" diameter	(0-5/acre)
TPA1	Dwn Wood, 1-2.9" diameter	(0-10/acre)
TPAPCTSL	% Slash per Dwn Wood <3"	(0-88%)
TPANS35	Dwn Wood, Nat. Sound 3-5.9"	(0-8/acre)

TPANR35	Dwn Wood, Nat. Rotten 3-5.9"	(0-8/acre)
TPASS35	Dwn Wood, Slash Sound 3-5.9"	(0-7/acre)
TPASR35	Dwn Wood, Slash Rotten 3-5.9"	(0-4/acre)
TPANS68	Dwn Wood, Nat. Sound 6-8.9"	(0-8/acre)
TPANR68	Dwn Wood, Nat. Rotten 6-8.9"	(0-5/acre)
TPASS68	Dwn Wood, Slash Sound 6-8.9"	(0-6/acre)
TPASR68	Dwn Wood, Slash Rotten 6-8.9"	(0-6/acre)
TPANS911	Dwn Wood, Nat. Sound 9-11.9"	(0-3/acre)
TPANR911	Dwn Wood, Nat. Rotten 9-11.9"	(0-9/acre)
TPASS911	Dwn Wood, Slash Sound 9-11.9"	(0-3/acre)
TPASR911	Dwn Wood, Slash Rotten 9-11.9"	(0-9/acre)
TPANS12	Dwn Wood, Nat. Sound 12-19.9"	(0-8/acre)
TPANR12	Dwn Wood, Nat. Rotten 12-19.9"	(0-18/acre)
TPASS12	Dwn Wood, Slash Sound 12-19.9"	(0-11/acre)
TPASR12	Dwn Wood, Slash Rotten 12-19.9"	(0-17/acre)
TPANS20	Dwn Wood, Nat. Sound >20"	(0-13/acre)
TPANR20	Dwn Wood, Nat. Rotten >20"	(0-20/acre)
TPASS20	Dwn Wood, Slash Sound >20"	(0/acre)
TPASR20	Dwn Wood, Slash Rotten >20"	(0-66/acre)
TPANAT	Dwn Wood, Natural Any Size	(0-33/acre)
TPASLA	Dwn Wood, Slash Any Size	(0-79/acre)
TPATOT	Dwn Wood, Total	(.6-82/acre)
TPAFD	Fuel Depth	(.6-11ft)
CVDW	Dwn Wood, coeff. of var. 8 transects	(0-2)
FPA0	Dwn Wood, <.25" diameter	(0-45 ft^3/acre)
FPA14	Dwn Wood, .25-.9" diameter	(0-342 ft^3/acre)
FPA1	Dwn Wood, 1-2.9"	(0-835 ft^3/acre)
FPANS3	Dwn Wood, Nat. Sound 1-5.9"	(0-634 ft^3/acre)
FPANR3	Dwn Wood, Nat. Rotten 1-5.9"	(0-874 ft^3/acre)
FPASS3	Dwn Wood, Slash Sound 1-5.9"	(0-553 ft^3/acre)
FPASR3	Dwn Wood, Slash Rotten 1-5.9"	(0-382 ft^3/acre)
FPANS6	Dwn Wood, Nat. Sound 6-8.9"	(0-621 ft^3/acre)
FPANR6	Dwn Wood, Nat. Rotten 6-8.9"	(0-561 ft^3/acre)
FPASS6	Dwn Wood, Slash Sound 6-8.9"	(0-488 ft^3/acre)
FPASR6	Dwn Wood, Slash Rotten 6-8.9"	(0-615 ft^3/acre)
FPANS9	Dwn Wood, Nat. Sound 9-11.9"	(0-260 ft^3/acre)
FPANR9	Dwn Wood, Nat. Rotten 9-11.9"	(0-989 ft^3/acre)
FPASS9	Dwn Wood, Slash Sound 9-11.9"	(0-236 ft^3/acre)
FPASR9	Dwn Wood, Slash Rotten 9-11.9"	(0-970 ft^3/acre)
FPANS12	Dwn Wood, Nat. Sound 12-19.9"	(0-630 ft^3/acre)
FPANR12	Dwn Wood, Nat. Rotten 12-19.9"	(0-1938 ft^3/acre)
FPASS12	Dwn Wood, Slash Sound 12-19.9"	(0-916 ft^3/acre)
FPASR12	Dwn Wood, Slash Rotten 12-19.9"	(0-1826 ft^3/acre)
FPANS20	Dwn Wood, Nat. Sound >20"	(0-1081 ft^3/acre)

FPANR20	Dwn Wood, Nat. Rotten >20"	(0-2139 ft^3/acre)
FPASS20	Dwn Wood, Slash Sound >20"	(0 ft^3/acre)
FPASR20	Dwn Wood, Slash Rotten >20"	(0-7003 ft^3/acre)
FPANAT	Dwn Wood, Natural Any Size	(.32-3122 ft^3/acre)
FPASLA	Dwn Wood, Slash Any Size	(0-8319 ft^3/acre)
FPATOT	Dwn Wood, Total	(42-8601 ft^3/acre)
SB1	SBE value, View 1	(-113 to148 SBE)
SB2	SBE value, View 2	(-113 to 135 SBE)
SB3	SBE value, View 3	(-102 to 123 SBE)
SB4	SBE value, View 4	(-118 to 130 SBE)
PP512	Ponderosa Pine 5-12" dbh	(0-727 no./acre)
PP1224	Ponderosa Pine 12-24" dbh	(0-198 no./acre)
PP1624	Ponderosa Pine 16-24" dbh	(0-74 no./acre)
PP24PLUS	Ponderosa Pine > 24" dbh	(0-18 no./acre)
PP144	Ponderosa Pine <5' high	(0-4100 no./acre)
PPLT5	Ponderosa Pine <5" dbh	(0-0-4700 no./acre)
PP524	Ponderosa Pine 5-24" dbh	(0-743 no./acre)
OA5PLUS	Oak > 5"	(0-485 no./acre)
OA512	Oak 5-12"	(0-0 no./acre)
OA12PLUS	Oak >12"	(0-66 no./acre)
OATOTAL	Total Oak	(0-8104 no./acre)
PDGANDF	Grass and Forbs herbage weight	(0-358 lbs.)
CCGANDF	Grass and Forbs canopy cover	(0-55%)
PDGANDS	Grass and Shrubs herbage weight	(.6-224 lbs.)
CCGANDS	Grass and Shrubs canopy cover	(0-37%)
FPA141	Dwn Wood, .25" to 2.9" dia	(0-1066 ft^3/acre)
FPA312	Dwn Wood, 1" to 11.9" dia	(0-1720 ft^3/acre)
FPA12PLS	Dwn Wood, 12" to >20" dia	(0-7003 ft^3/acre)
FPA3PLUS	Dwn Wood, 1" to >20" dia	(0-8473 ft^3/acre)
FPALT3	Dwn Wood, <.25" to 2.9" dia	(0-1068 ft^3/acre)
FPASS	Dwn Wood, Slash Sound 1" to >20"	(0-1338 ft^3/acre)
FPASR	Dwn Wood, Slash Rotten 1" to >20"	(0-7925 ft^3/acre)
FPANS	Dwn Wood, Nat. Sound 1" to >20"	(0-1207 ft^3/acre)
FPANR	Dwn Wood, Nat. Rotten 1" to >20"	(0-2738 ft^3/acre)
FPAPCTSS	Ratio Sound Slash 1" to >20" to all	(0-1.0)
PP5PLUS	Ponderosa Pine, 5" to 23.9" dbh	(2-743/acre)
PTSBE	Average of SB1, SB2, SB3, SB4	(-83 to 98)
IASP	Recoded Aspect	(1-9)
HGTMAX	Herbage maximum height	(.80-38 ft^3/acre)

Appendix D:

Codebook for NEMODEL Stimulus Set

Title: NE Model Codebook
Field Tour Pilot Study

Date: 1991

Contact: Paul Gobster
North Central Research and Experiment Station
845 Chicago Ave., Suite #225
Evanston, IL 60202-2537
Phone: (847) 866-9311 (x16)
Fax: (847) 866-9506

Description:

Thirty-three areas were photographed from Northeast Forest Experiment Station study sites as part of an aesthetic assessment pilot project in the development of the Northeast Decision Model. Between 1 and 4 photographs were taken to represent each area, yielding a total of 88 slides. The author collected mensuration data for each site and subjectively rated each site across 8 theoretically specified stand attributes (e.g., canopy continuity and openness). Subjects rated each slide for "scenic quality," and these ratings were then averaged across subjects and across the slides comprising each area. Scenic beauty judgments were then systematically compared to the 8 subjective rating scales as well as 15 biophysical measures using bivariate correlations.

Citations:

Gobster, P. (1991). NE model field tour aesthetic analysis: Pilot study of photo ratings. Chicago, IL: North Central Experiment Station.

Variable List

Varname	Variable Name	Measurement
CASE	Slide Number	(1-88)
PHOTO$	Photo Name	(Site, Stand, Number)
SBLAB	Mean score rating	(Personal Rating 1-10)
SBE	Scenic Beauty Estimate score	SBE method (N=5)
STAND$	Stand name	(Site, Stand)
CANCONT	Canopy Continuity	Subjective field evaluation
NATURAL	Natural Appearance	(1= very low to 5= very high)
BIGTREE	Large-tree Look	"
DISTURB	Disturbed Look	"
SCREEN	Screening	"
OPEN	Openness	"
INVAR	Within stand variety	"
LVAR	Landscape variety	"
SBFIELD	Mean Score Rating	(Personal Rating 1-10)
TREESAC	No. Trees/ac	(14-1433 no. trees/acre)
BA	Basal Area/ac	(8-192 ba/acre)
RELDENS	Relative Density	(10-100)
MDIAM	Median Diameter	(3-18")
DIAMERCH	Med. Diam. Merchantables	(7-19")
QUADIAM	Quadratic Stand Diameter	(2-13")
MAXDBH	Max. Tree dbh	(2-50")
BA17	Basal Area/ac >17" dbh	(0-117 ba/acre)
BA11	Basal Area/ac >11" dbh	(0-151 ba/acre)
BA6	Basal Area/ac <6" dbh	(0-78 ba/acre)
NTREES6	No. Trees/ac <6" dbh	(0-1590 no./acre)
Q	Q factor	(1.3-1.4)
NSEEDAC	Total No. Seedlings/ac	(11-96600 no./acre)
NSEED3	No. Seedlings/ac > 3' tall	(2200-21800 no./acre
NSEED5	No. Seedlings/ac > 5' tall	(800-17900 no./acre)

Appendix E:

Codebook for SEASON Stimulus Set

Title: Seasonal Scenic Value and Forest Structure
Northeastern Hardwood Stands

Date: 1984

Contact: James F. Palmer
College of Environmental Science and Forestry
State University of New York, Syracuse
1 Forestry Drive
Syracuse, NY 13210
Phone: (315) 470-6548

Description:

Six sites throughout forested areas in Cortland and Onondaga Counties in upstate New York were identified for being representative of Northern hardwood composition and a variety of post harvest conditions (ranging from 1-13 years). 23 views representing all six sites were photographed during each season of the year. Photographs were taken using a single-lens reflex camera with a 35mm lens on overcast days to reduce the influence of shadow contrast across seasons. Mensuration data were collected from a 64 degree wedge that began at the photo point and was 30 meters deep. Slides were rated for the "scenic value" of each scene by the same group of students four times over a one year period. Forest structure measurements were then independently used to predict the scenic value of each scene for a given season.

Citations:

Palmer, J.F. (1984). The influence of season and time since harvest on forest aesthetics. (USDA Cooperative State Research Service, McIntire-Stennis Cooperative Forestry Research Program No. C400/C100-1078). SUNY College of Environmental Science and Forestry, Syracuse, NY.

Palmer, J.F. (1990). Aesthetics of the northern hardwood forest: Influence of season and time since harvest. In T. More, M. Donnelly, A Graefe, & J. Vaske (Eds.), Proceedings of the 1990 Northeastern Recreation Researchers Symposium (Gen. Tech, Rep. NE-145, pp. 185-190). USDA Forest Service, Northeastern Forest Experiment Station: Radnor, PA.

Palmer, J.F., & Sena, K.D. (1992). Seasonal scenic value and forest structure in northeastern hardwood stands. In G.A. Van Der Stope (Ed.), Proceedings of the 1992 Northeastern Recreation Researchers Symposium (Gen. Tech, Rep. NE-176, pp. 115-121). USDA Forest Service, Northeastern Forest Experiment Station: Radnor, PA